SHREC'08 Entry: 3D Shape Searching using Object Partitioning

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Abstract

In this paper we propose a novel algorithm for 3D shape searching based on the visual similarity by cutting the object into sections. This method rectifies some of the shortcomings of the visual similarity based methods, so that it can better account for concave areas of an object and parts of the object not visible because of occlusion. As the first step, silhouettes of the 3D object are generated by partitioning the object into number of parts with cutting planes perpendicular to the view direction. Then Zernike moments are applied on the silhouettes to generate shape descriptors. The distance measure is based on minimizing the distance among all the combinations of shape descriptors and then these distances are used for similarity based searching. We have performed experiments on the Princeton shape benchmark and the Purdue CAD/CAM database, and have achieved results comparable to some of the best algorithms in the 3D shape searching literature.

Index Terms: J.6.1 [Computer-aided Engineering]: Computer-aided design— [I.5.4]: Pattern Recognition—Applications

1 Introduction

3D objects are widespread and used in many diverse areas such as computer graphics, computer aided design, cultural heritage, medical imaging, structural biology, and other fields. Large numbers of 3D models are created every day using 3D modeling programs and 3D scanners and many are stored in publicly available databases. Understanding the 3D shape and structure of these models is essential to many scientific and engineering activities. These 3D databases require methods for storage, indexing, searching, clustering, and retrieval to be used effectively. Content based 3D shape retrieval is an active area of research in 3D community.

We propose an algorithm for 3D shape searching based on visual similarity by cutting the object into multiple parts which rectifies some of the shortcomings of the visual similarity based methods. The algorithm better accounts for concave areas of an object and for parts of the object not visible because of occlusion. 1) Silhouettes of the 3D object are generated by cutting the object into several different parts with cutting planes perpendicular to the view direction. 2) These silhouettes of different parts of an object are used for generation of the shape descriptor using Zernike moments. 3) The distance measure is based on minimizing the distance among all the combinations of the shape descriptors and then these distances are used for similarity based retrieval. By cutting objects into smaller parts we can also perform partial matching which is useful in many circumstances[5] where it is not necessary to match the whole object. We have performed experiments with our algorithm on the Princeton shape benchmark and the Purdue CAD/CAM database and we have achieved results comparable to some of the best algorithms in the 3D shape searching literature.

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IEEE International Conference on Shape Modeling and Applications 2008
4 - 6 June, Stony Brook, New York, USA
978-1-4244-2261-6/08/$25.00 ©2008 IEEE

The rest of the paper is organized as follows, next section describes the previous work in this domain and then we will describe the shape partitioning and its benefits. The method to generate the descriptor and calculate the distance between two 3D objects are described in section 4 and 5 respectively. Finally, some of the results are presented to show the effectiveness of our novel algorithm and then conclusions are provided.

2 Previous work

In [4] and [13], the authors developed a descriptor based on the silhouettes from multiple directions for visual similarity based comparison. Initial methods proposed for 3D object searching were based on the histograms [3] and [10]. Although these methods are very simple and fast to compute, the results were not that promising. In [7] Laga et al. discussed the generation of a descriptor for 3D shape comparison using spherical wavelet transforms. Recently in [9] some work has been done to define shape features using Krawtchouk moments. In [12] Shilane et al discussed the creation of the Princeton Shape Benchmark, and analyzed some of the contemporary algorithms for 3D shape retrieval.

In [6] authors discussed methods to compare images based on the Zernike moments and compared the performance of Zernike moments with other type of image similarity measures.

3 Shape partitioning

In order to capture more details about the cancave and occluded parts of an object, we propose to partition the object into several parts. Then these 3D objects can be considered as composition of these pieces. We can identify individual objects on the basis of these smaller parts. These subparts can be individually processed to get shape features which can be optimally combined to form a unique feature vector for the whole object.

Each plane partitions the 3D object exposing the cavity of the object. An image taken at this point can be used to construct a feature vector which can give considerably better performance in case of the objects which have concave areas or where part of the object is not visible because of occlusion. This is particularly useful for the CAD/CAM(Computer Aided Design) models. To consider the benefit of this method just consider that we need to calculate the feature of a cup. Now if we assume we are using the visual similarity based method [4], then we are only taking the views of the cup from several angles. So we will miss the concave parts, because the cup will only be modeled as a flattened surface. But if we model the cup by our algorithm we will be able to create views which will show the concave part of the cup with better and more accurate info about the structure of the cup. This can be observed in the figure 1.

By keeping the viewport fixed in the space, we rotate the object and partition it into separate sections by using planes that cut the object. The cutting planes are parallel to the viewport plane and form the near and far planes for the viewport and in turn dissect the 3D object. This is done from multiple angles and with different positions of the dissecting planes. we rotate the object on it's center along three principal axis and on 60 degrees on XY, XZ and YZ axis. Our algorithm depends on the planar cuts made at equidistant positions, so the object will be visible between the near and far planes, which cut the object as shown in the Figure 2.

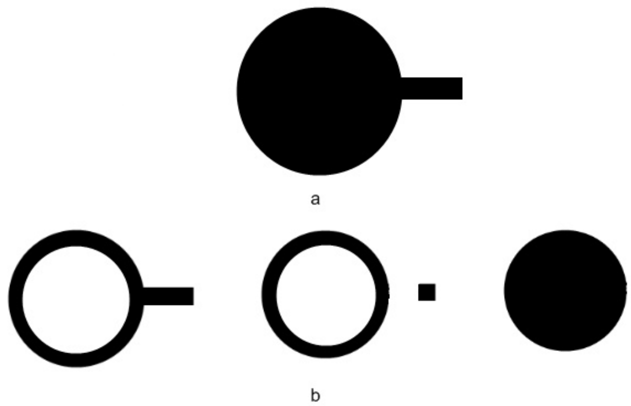

Figure 1: Cup (a) when seen using the LFD algorithms and (b) when seen by partitions algorithms.

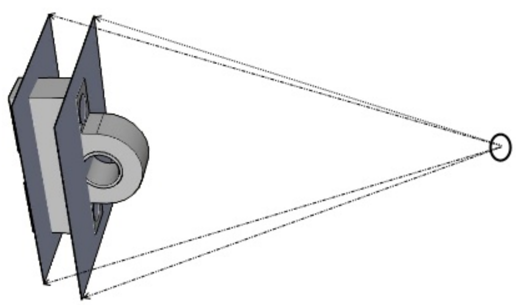

Figure 2: CAD part and it's partitions.

4 Object descriptor

Each image set is basically composed of snapshots of object partitions from predefined directions. For each image we calculate the Zernike moments which are then sequentially combined to form a single descriptor for that object. These descriptors form the object feature vectors, which will be compared with other object's descriptors to match their similarity.

$$\begin{aligned} CF_{xf} &= [F_x^1; F_x^2; ......; F_x^{N-1}; F_x^N] \\ CF_{xr} &= [F_x^N; F_x^{N-1}; ......; F_x^2; F_x^1] \\ CF_{yf} &= [F_y^1; F_y^2; ......; F_y^{N-1}; F_y^N] \\ CF_{yr} &= [F_y^N; F_y^{N-1}; ......; F_y^2; F_y^1] \\ CF_{zf} &= [F_z^1; F_z^2; ......; F_z^{N-1}; F_z^N] \\ CF_{zr} &= [F_z^N; F_z^{N-1}; ......; F_z^2; F_z^1] \end{aligned} \tag{1}$$

5 Feature comparison

The final distance is the minimum of the distance between all the combinations of distances calculated from a feature set of an object. This is done in two steps.

1. We calculate the distance between the features based on the L1 norm distance between the individual shape descriptors from each direction.

$$L_1(v_1, v_2) = |v_1 - v_2| \tag{2}$$

2. We find the smallest distance between the two descriptors. The smallest of the distance is stored and the corresponding descriptors are eliminated from the search in the next stage until we find the next smallest pair of descriptors in terms of distances. The minimum distances are then summed to form the final distance measure between two objects.

$$\delta(o_1, o_2) = \sum \min(L1(CF_i, CF_2)) \tag{3}$$

6 Conclusion

The algorithm presented here is extensible and we have explored a few options about the parameters, but still there is room for more improvement in terms of the number of the cuts, the rotation angles and the type of moments. Some of the former techniques for 3D shape searching can be reformulated with this algorithm, which will increase their accuracy. Further improvements are possible by extending this algorithm by using hybrid feature vectors, which will improve the accuracy a bit further.

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